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Integrating 3D printing, IoT, and AI for precision agriculture: automated sensing and smart farming applications

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Abstract

Precision agriculture utilizes data-driven, site-specific management practices to optimize inputs, including seeds, fertilizers, and irrigation, thereby enhancing yields, reducing costs, and minimizing environmental impacts. This review provides a comprehensive analysis of recent advancements in 3D printing, the Internet of Things (IoT), and artificial intelligence (AI), and their integration for improving farm management. Three-dimensional printing enables the fabrication of customized sensors and components for accurate soil and crop monitoring. IoT-based sensor networks support real-time data collection on key agricultural parameters, while AI and image-processing techniques deliver advanced analytics for early detection of nutrient deficiencies, diseases, and stress conditions. Collectively, these technologies drive the development of automated nutrient and resource management systems that enhance efficiency, sustainability, and decision-making in farming. The review also addresses current limitations, including cost, technical expertise, and durability challenges, while emphasizing prospects and the transformative potential of integrating digital technologies with agricultural practices to achieve environmentally friendly and resource-efficient farming.

Keywords: *precision agriculture, 3D printing, IoT, artificial intelligence, image processing, modern farming, automated sensors*

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1. Introduction

Precision agriculture is a leading-edge farming technique that employs advanced technologies to optimize agricultural practices [1]. Precision agriculture utilizes data-driven techniques to enhance the efficiency, production, and sustainability of agricultural practices, as opposed to conventional farming, which relies on uniform treatments and manual labor [2]. The advent of technology such as 3D printing, the Internet of Things, and artificial intelligence has significantly amplified the capabilities of precision agriculture.

Three-dimensional printing technology allows for the creation of customized equipment and sensors that may be tailored to fit specific agricultural needs. As sensors produced through 3D printing can be precisely designed to effectively monitor soil moisture, nutrient concentrations, and environmental factors [3]. IoT technology enables the seamless connectivity of various devices and sensors through the internet, enabling immediate data collection and communication [4]. IoT systems in agriculture may monitor many characteristics, such as soil fertility, meteorological conditions, and crop development [5]. These systems provide farmers with real-time data, enabling them to make informed decisions. The evaluation of huge datasets and high-resolution images is conducted using artificial intelligence algorithms and modern image processing techniques. The main goals of this analysis are to detect patterns, diagnose crop health issues, and predict crop and field conditions. These technologies expedite the early detection of problems such as pest infestations, diseases, and nutrient deficiencies, allowing for immediate action [6].

The integration of 3D printing, IoT, and AI in precision agriculture has drastically impacted the techniques employed in current farming. Precision agriculture seeks to optimize the efficiency of resources, enhance productivity, and minimize the environmental footprint through the utilization of advanced technologies [7]. The positive impact of these technologies lies in their ability to provide precise, current data and advanced analytical capabilities. This empowers farmers to make informed decisions by utilizing actionable insights. Precision agriculture employs automated technologies and data-driven interventions to improve the efficiency, sustainability, and profitability of agricultural operations. Furthermore, by reducing waste and improving energy efficiency, these technologies actively contribute to cost reduction, hence enhancing the economic feasibility of farming. The integration of 3D printing, IoT, and AI in precision agriculture signifies a substantial shift towards a more efficient, environmentally friendly, and adaptable agricultural future. This has extensive implications for securing food security and preserving the environment. Over the past three decades, the evolution of precision agriculture technologies has been marked by steady innovation, from GPS-based equipment to fully integrated AI-IoT systems. **Table 1** highlights this progression, showcasing major milestones that have collectively shaped the current landscape of smart farming.

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Table 1 • Timeline of technological advancements in precision agriculture.

Year/period	Innovation/development	Technology involved	Impact on agriculture	References
1990s	GPS-guided tractors	Precision mechanization	Improved field navigation	[8]
Early 2000s	Remote sensing from satellites	Remote Sensing, GIS	Area-level crop monitoring	[9]
2010	Cloud-based farm management tools	ICT, Data platforms	Decision support and record-keeping	[10]
2012–2014	Drones for aerial imaging	UAVs, Image processing	Real-time crop health mapping	[11]
2015	IoT-enabled soil moisture sensors	IoT	Site-specific irrigation	[12]
2016	AI-powered pest detection algorithms	AI, Image processing	Proactive crop protection	[13]
2017–2018	Use of 3D printing for tool prototyping	3D printing	Cost-efficient tool and sensor development	[14]
2019	LPWAN (LoRa, NB-IoT) in rural farms	Wireless networking	Improved long-range sensor connectivity	[15]
2021	Blockchain in agri-supply chain	IoT + Blockchain	Secure and traceable food supply	[16]
2023–Present	Integrated AI-IoT-3D Printing smart systems	AI + IoT + 3D printing	Full automation in nutrient, irrigation, and pest control	[17]

This review study aims to investigate the coordinated application of 3D printing, IoT, and AI in precision agriculture, analyzing their collective impact on modern farming practices. The objective of this article is to offer an in-depth assessment of the most recent advancements in these technologies as they are applied in the field of precision agriculture. This analysis will delineate the distinct capabilities of each technology and scrutinize how their integration can provide substantial transformations in agricultural practices. Moreover, this study aims to assess the current implementation of these technologies in real-world agricultural settings, clarifying the tangible benefits they offer to farmers and agricultural professionals. This analysis seeks to offer ideas on how to overcome obstacles and achieve the full potential of precision agriculture by identifying and addressing important difficulties and restrictions related to the integration of these technologies. Moreover, its objective is to provide opportunities for future research and advancements that could boost the integration and efficacy of these technologies in enhancing agricultural productivity, sustainability, and resilience.

2. Literature review

The methodology for this review involved a systematic search across Scopus, Web of Science, and Google Scholar databases, using keywords such as 'Precision Agriculture,' 'AI in farming,' 'IoT sensors agriculture,' and '3D printing agriculture.' Studies published between 2010 and 2025 were included. The inclusion criteria focused on peer-reviewed articles reporting applications of AI, IoT, or 3D printing in agricultural systems, while non-peer-reviewed and non-agricultural studies were excluded to ensure relevance and quality. This systematic approach allowed for the comprehensive synthesis of prior research, highlighting integration pathways and identifying key advancements and challenges.

2.1. Three-dimensional printing in equipment

Three-dimensional printing technology has made considerable advancements in recent years, expanding its usefulness in other industries, including agriculture. Important progress has been made in the field of 3D printing with the creation of cost-effective and adaptable printers that can utilize a wide range of materials, including plastics, metals, and even biocompatible substances [18]. This adaptability enables the development of personalized agricultural implements and parts designed to meet precise farming requirements. Three-dimensionally printed sensors are capable of accurately assessing soil moisture, nutrient levels, and ambient variables with exceptional precision [19]. Another example of significant progress is the enhancement in the resolution and velocity of 3D printing procedures. The utilization of high-resolution 3D printing facilitates the creation of complex components suitable for delicate agricultural machinery. Quicker printing speeds contribute to a reduction in the time needed to manufacture essential parts. In addition, software improvements have enabled farmers and agricultural engineers to develop precise and efficient designs that promote agricultural production, owing to improved design capabilities [20].

Three-dimensional printing has been widely used in agriculture, significantly changing different parts of farming activities. An important use case involves the fabrication of customized tools and components [21]. Agricultural practitioners can create and produce customized instruments that are tailored to the individual needs of their crops and soil conditions. This capability results in the adoption of more effective and productive farming techniques [22]. As an illustration, irrigation systems can utilize 3D-printed nozzles that are tailored to distribute water with precision, minimizing water waste and enhancing crop productivity [23]. Prototyping and testing are also significant applications in this

field. Agricultural researchers and developers use 3D printing to hasten the process of developing and testing new tools and components, which shortens the innovation cycle. The ability to rapidly prototype allows for the creation of more efficient agricultural technology within a compressed timeframe.

Three-dimensional printing is utilized to manufacture substitute components for agricultural machinery. Three-dimensional printing provides a solution in isolated or rural locations with restricted access to replacement parts by allowing the manufacturing of necessary components on-site. This reduces downtime and maintenance expenses [24]. This feature is especially beneficial for small-scale farmers who may lack the means to maintain large inventories of spare parts. Although 3D printing has the potential to revolutionize agriculture, a number of barriers prevent its use. An essential obstacle is the upfront expense associated with procuring 3D printing equipment and supplies. Despite the fall in pricing, the investment required for small and medium-sized farms can still be significant. In addition, the maintenance and operation of 3D printers necessitate a specific degree of technical proficiency, which may not be easily accessible in all agricultural communities.

Another obstacle lies in the durability and appropriateness of 3D-printed components in demanding agricultural settings. Although progress has been made, many 3D-printed materials may still lack the same level of durability as conventionally manufactured parts, especially when subjected to severe weather conditions or intense usage. Continual research and improvement are required to enhance the durability of 3D-printed agricultural components due to this constraint. There are apprehensions regarding the standardization and control of 3D-printed agricultural products. It is essential to ensure that these items adhere to safety and quality requirements, although the regulatory structure is still developing. The presence of this uncertainty can hinder public acceptance and confidence in agricultural solutions that utilize 3D printing technology [1]. **Figure 1** illustrates the complete workflow of 3D printing applications in agriculture, starting from computer-aided design and material selection to prototyping, testing, and real-world implementation. This process highlights how customized irrigation nozzles, spare parts, and sensor housings can be rapidly designed and manufactured to suit field-specific requirements, thereby reducing costs and minimizing downtime.

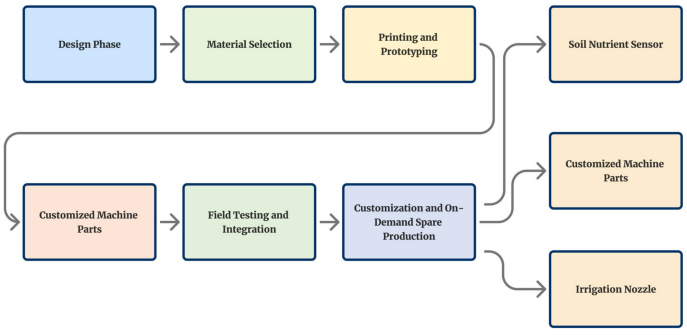

Figure 1 • Workflow of 3D printing applications in agriculture.

2.2. IoT in precision agriculture

The use of the IoT in precision agriculture has transformed farming methods by improving effectiveness, output, and ecological soundness [25]. The transition heavily relies on IoT sensor networks, which consist of interconnected sensors, devices, and data analytics tools. These networks gather and transmit up-to-date information on many agricultural factors, allowing farmers to make well-informed choices. Precision agriculture IoT sensor networks provide the capability to monitor a diverse array of environmental and soil variables. These networks generally consist of sensors that measure soil moisture, temperature, humidity, light intensity, and nutrient levels. Advanced sensors are capable of detecting plant health indicators, including chlorophyll content and pest infestations. The sensors collect data, which is then transferred to central databases using wireless communication protocols including Zigbee, LoRa, and NB-IoT. This enables real-time analysis and decision-making. A notable progress in IoT sensor networks is the emergence of low-power wide-area networks (LPWANs), which enable long-distance communication while consuming minimal energy. This method is especially advantageous for agricultural activities on a large scale, as sensors are spread out over vast areas [26]. Furthermore, the incorporation of AI and ML algorithms with IoT sensor data has enhanced predictive analytics, facilitating proactive actions in crop management and disease control [27].

Soil monitoring and management: IoT sensor networks offer comprehensive data on soil conditions, enabling accurate control of irrigation and fertilizer. The use of soil moisture sensors to enhance watering schedules, reduce water waste, and guarantee crops receive adequate hydration. Climate monitoring involves the use of sensors to measure temperature, humidity, and light intensity. These sensors are used to create microclimate models, which provide valuable information for determining optimal planting and harvesting schedules [28]. This information is vital for optimizing crop production and mitigating the effects of unfavorable weather conditions. IoT sensor networks enable crop health monitoring by enabling the ongoing detection of anomalies like pest infestations and nutrient deficits. Utilizing sensors for early detection can result in timely interventions that reduce crop loss and improve yield quality [29].

Precision animal farming: In addition to managing crops, IoT sensor networks are also used in animal farming. Sensors monitor animal health, mobility, and environmental conditions in barns and pastures. These data enable farmers to maintain the most favorable living conditions for cattle, thereby enhancing productivity and welfare. IoT sensor networks play a crucial role in the operation of automated farming equipment, such as self-driving tractors and drones [30].

Although there are many advantages, the implementation of IoT sensor networks in precision agriculture encounters various obstacles. These factors encompass the expensive nature of sensor placement, anxieties around data privacy, and the requirement for reliable internet connectivity in rural regions [31]. To tackle these difficulties, it is necessary for technology developers, legislators, and farmers to work together in order to develop IoT solutions that are both cost-effective and secure [32]. Future developments in IoT sensor networks are anticipated to prioritize the enhancement of sensor precision, the reduction in power consumption, and the improvement of data analytics capabilities. Implementing blockchain technology has the potential to improve data security and traceability in agricultural supply chains [33].

The implementation of IoT sensor networks has greatly enhanced precision agriculture by offering up-to-the-minute data and valuable insights to optimize farm operations. These technologies have the capacity to revolutionize agricultural operations, enhancing their sustainability and productivity. Continual innovation and tackling present obstacles will bolster the acceptance and efficacy of IoT in agriculture [34]. **Figure 2** presents the architecture of IoT sensor networks in precision agriculture. It illustrates how soil, climate, and crop health sensors communicate through wireless protocols to a central gateway and cloud platform. The integration of AI/ML analytics enables predictive decision-making for irrigation, nutrient management, disease detection, and livestock health monitoring, ensuring resource optimization and sustainability in farming practices.

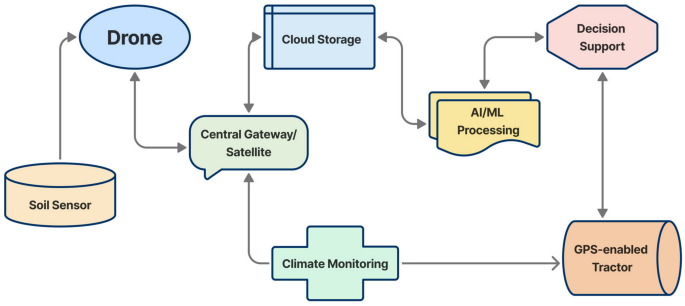

Figure 2 • IoT sensor network architecture in precision agriculture.

2.3. AI and image processing

The incorporation of AI and image processing in agriculture has greatly improved the surveillance of crops and the administration of farms. These technologies offer a comprehensive and precise assessment of crop health, growth, and environmental factors, empowering farmers to make well-informed choices and enhance their operations [35].

AI technology, including machine learning and deep learning (DL) algorithms, is widely employed to analyze data from diverse sources such as satellite imaging, drones, and ground sensors. AI algorithms analyze extensive datasets to detect trends and provide forecasts regarding crop conditions, prospective yield, and occurrences of pest infestations. An important use of AI is in predictive analytics, which involves analyzing historical and real-time data to forecast weather conditions, pest outbreaks, and crop diseases. Farmers can use this technology to implement proactive strategies, such as modifying irrigation schedules or spraying pesticides with precision, in order to minimize waste and enhance efficiency [36, 37]. While high-resolution drone and satellite imagery can provide detailed insights, in practice, many farm management tools operate at resampled resolutions of 8–10 m to balance accuracy with cost and practicality [38].

Image processing techniques encompass the act of obtaining, examining, and comprehending visual data obtained by cameras mounted on drones, satellites, or stationary installations. These strategies aid in the surveillance of different crop metrics, including leaf area index, chlorophyll content, and plant height [39]. Disease detection involves the utilization of AI algorithms to analyze high-resolution photos obtained from drones or satellites, with the aim of identifying initial indications of diseases on plant leaves and stems. These algorithms have the capability to detect disease patterns that are not discernible to the unaided eye, facilitating prompt intervention and minimizing crop damage [40]. Image processing facilitates the differentiation of crops and weeds. AI-based image analysis systems provide the capability to precisely detect and classify various types of weeds, enabling the application of herbicides to be focused and specific. By employing precision, the quantity of chemicals utilized is decreased, resulting in a reduction in environmental impact [41]. Image processing techniques utilize crop photos to estimate yield by evaluating characteristics such as fruit count, size, and distribution. These estimations assist farmers in efficiently organizing their crops and overseeing supply chains. Multispectral and hyperspectral imaging techniques are employed to observe and assess the nutritional condition of plants. The images offer valuable data regarding nutrient deficits, allowing for accurate fertilization techniques that improve both crop growth and yield [42].

Notwithstanding the notable progress, numerous obstacles impede the extensive implementation of AI and image processing in agriculture [43]. These factors include the expensive nature of sophisticated imaging equipment, the necessity of extensive datasets for training artificial intelligence models, and the demand for reliable internet connectivity in rural regions [44]. To tackle these difficulties, it will be necessary to devise affordable technologies, generate comprehensive agricultural databases, and enhance the internet infrastructure in rural areas. Subsequent investigations are anticipated to prioritize the enhancement of precision and dependability in AI models and picture-processing methodologies [45]. By incorporating these technologies into IoT and blockchain, the security and traceability of data can be significantly improved, resulting in increased efficiency and transparency in farm management [46]. Although artificial intelligence offers powerful tools for data analysis, prediction, and decision support in agriculture, it is not without limitations. Agricultural systems are influenced by highly dynamic and uncertain variables, including unpredictable weather events, pest outbreaks, soil biological activity, and management practices that vary from farm to farm. AI models operate on training datasets and may struggle when exposed to novel or rapidly changing conditions. AI outputs are inherently probabilistic, meaning they provide likelihood-based insights rather than absolute precision. Farmers must therefore treat AI as a decision-support system, integrating its recommendations with field observations, expert knowledge, and adaptive management strategies [47, 48]. Future research should focus on improving the transparency of AI models, developing uncertainty quantification methods, and designing farmer-friendly interfaces that communicate recommendations in practical terms.

2.4. Automated farm management

The prevalence of automated agriculture management systems has increased, offering innovative solutions for various activities, including plowing, planting, spraying, harvesting, and fertilizer management. These systems employ the latest innovations, such as robotics, GPS, and IoT, to enhance precision, efficiency, and eco-friendliness in agricultural practices [26].

Tillage automation: Autonomous tractors equipped with GPS and AI are utilized in automated tillage systems to achieve exact soil preparation. These systems can enhance the depth and arrangement of tillage, resulting in a decrease in soil compaction and energy usage. Empirical studies have shown that the implementation of automated tillage can enhance operational efficiency and promote soil health through the maintenance of consistent tillage techniques [49].

Automated sowing: Precision sowing systems utilize robotic planters and GPS-guided equipment to spread seeds at the most favorable depths and distances. These technologies guarantee consistent seed dispersion and optimize germination rates. Research suggests that the implementation of automated sowing techniques improves the consistency and productivity of crops by minimizing mistakes and variations caused by human involvement in the planting process [50].

Spraying automation: Automated spraying systems, such as drones and robotic sprayers, utilize advanced technology to accurately administer pesticides and fertilizers. These systems utilize sensor data to identify insect infestations and nutritional deficits, enabling precise treatments that minimize the use of chemicals and reduce environmental impact. Field trials demonstrate substantial decreases in pesticide utilization and enhanced crop vitality through the implementation of automated spraying [51].

Automated harvesting: Robotic harvesters, equipped with artificial intelligence and machine vision technology, have the capability to detect mature crops and carry out targeted harvesting. These devices decrease labor expenses and enhance the rate of harvesting. Studies have shown that automated harvesting systems are efficient in selecting fruits and vegetables with minimal harm, hence improving total productivity [52].

Nutrient management: Automated systems for nutrient management utilize sensors to monitor soil and plant nutrient levels and make adjustments to fertilizer accordingly. These systems have the ability to accurately supply nutrients at the exact time and location required, which enhances plant development and minimizes waste. Studies have shown that the implementation of automated nutrient management systems leads to increased crop yields and improved efficiency in nutrient utilization. It is important to clarify that sensors in agricultural systems do not provide absolute or exact values for every individual plant or soil point, but rather deliver indicative and zone-based information [53]. Due to the inherent variability of soils, microclimates, and biological conditions, measurements often fluctuate. For this reason, raw sensor outputs require normalization and calibration across space and time. Artificial intelligence and machine learning models play a key role in this process by filtering noise, identifying trends, and converting uncertain or variable data into actionable recommendations. Thus, rather than achieving perfect precision, the goal is to use sensor networks in combination with AI analytics to improve decision-making at the field or management-zone level [54].

2.5. Efficacy in field trials

Empirical studies have consistently demonstrated that automated farm management systems significantly improve agricultural output and sustainability [55]. Automated tillage and sowing systems have been shown to decrease fuel consumption and labor expenses, while simultaneously enhancing soil structure and crop emergence rates. Automated spraying systems have successfully reduced pesticide consumption by up to 30%, promoting safer and more environmentally sustainable farming methods [11].

Automated harvesting systems have demonstrated notable efficacy in labor-intensive crops such as fruits and vegetables by substantially diminishing the need for manual labor and enhancing harvesting efficiency [56]. Automated fertilizer management systems have been shown to enhance crop nutrient absorption and productivity, leading to the adoption of more sustainable fertilization methods.

2.6. Technical and operational barriers in smart farming

Although there are advantages, numerous obstacles impede the extensive implementation of automated farm management systems. Significant obstacles include the high upfront expenses, the requirement for specialized knowledge, and apprehensions over the dependability of the equipment. Moreover, small-scale farmers may encounter challenges in rationalizing their expenditure on these sophisticated technologies [57].

Future research and development should prioritize enhancing the affordability and user-friendliness of automated systems. By enhancing the interoperability of various systems and incorporating advanced data analytics, their effectiveness can be further improved. Effective collaboration among technology suppliers, agricultural researchers, and farmers is crucial for tackling these difficulties and encouraging the widespread implementation of automated farming systems [58].

Automated farm management systems have demonstrated significant potential for improving the effectiveness and long-term viability of agricultural activities [30]. Field trials confirm the efficacy of these methods in many agricultural activities, such as plowing, planting, applying pesticides, gathering crops, and managing nutrients. In order to fully harness the transformative power of these technologies in revolutionizing agriculture, it is imperative to maintain a constant drive for innovation and effectively tackle existing issues [59].

3. Advancement and current methodology

3.1. Research design

The general research framework integrates the creation and evaluation of innovative 3D-printed sensors, the establishment of an IoT network, and the utilization of AI and image processing methods to improve the automation of agricultural activities [60]. The approach comprises several stages: the design and production of sensors, the development of a network, the training of an AI model, and the integration of these technologies into farm management systems. Field trials are performed to assess the efficacy and efficiency of the system [61].

3.2. Development of 3D-printed sensors

The design procedure for 3D-printed sensors commences with carefully choosing materials that possess both durability and sensitivity to specific environmental conditions, such as soil moisture,

temperature, and nutrient levels [62]. When creating intricate sensor models for a high-resolution 3D printer, CAD software is helpful. Following the manufacturing process, every sensor is subjected to stringent evaluation in controlled laboratory environments to guarantee precision and dependability [63]. Calibration is achieved by comparing the sensor outputs with conventional measurement equipment, and any differences are resolved by iterative design adjustments.

3.3. IoT network setup

Implementing the IoT network requires strategically positioning sensors around the farm to provide extensive coverage. The sensors are programmed to wirelessly broadcast data to a central hub utilizing communication protocols such as Zigbee, LoRa, or NB-IoT [64]. The network setup comprises the subsequent steps: Conduct a site survey to determine the most suitable positions for sensors, taking into account the farm's topography and layout. Affix sensors in assigned locations, guaranteeing secure placement and accurate alignment. Establishing communication links between sensors and the central hub, establishing data transmission intervals, and guaranteeing reliable connectivity. Establish a data management infrastructure to gather, store, and analyze incoming data, enabling immediate monitoring and informed decision-making [65].

3.4. AI and image processing implementation

The implementation of artificial intelligence and image processing in precision agriculture involves a systematic and technologically layered approach aimed at enhancing real-time crop health monitoring and decision-making. The process begins with the acquisition of high-resolution images using aerial and ground-based imaging systems. Drones equipped with RGB, multispectral, or hyperspectral cameras fly over the crop fields at regular intervals, capturing detailed visual data that reflects plant morphology, coloration, and overall canopy health [66]. This visual record enables a granular view of crop development far beyond what human inspection can offer.

After acquisition, the image data undergoes an essential preprocessing phase to prepare the visual information for accurate machine interpretation. Preprocessing techniques include applying filters to reduce noise, adjusting brightness and contrast, normalizing image sizes and orientations, and using techniques such as segmentation and edge detection to isolate regions of interest [67]. This phase is critical not only for enhancing visual clarity but also for ensuring that the subsequent AI model can focus on relevant features without being misled by background artefacts or image inconsistencies.

Following preprocessing, the system enters the learning stage, where AI models are trained to identify patterns and classify conditions based on the processed images. Convolutional neural networks (CNNs), a subset of deep learning algorithms particularly effective in image analysis, are commonly employed for this task [68]. These models are trained using large datasets of annotated images that represent various plant conditions.

Once trained, the AI model is deployed into an integrated image processing system capable of analyzing live data streams [69]. This integration can be extended to autonomous machines, allowing for closed-loop operations where the system not only detects issues but also initiates responsive interventions. The integration also supports mobile and web interfaces, enabling farmers and agronomists to remotely access real-time insights and take timely actions. To ensure the system performs accurately under real-world agricultural conditions, a rigorous validation phase is conducted. Discrepancies between predicted and actual conditions help identify areas for model refinement, making the AI model more generalizable and scalable across different agro-climatic zones [70].

3.5. Automated farm operations

Using sensors, AI, and IoT technology together makes it easier to set up and run automated farm systems that perform many important farming tasks better. Self-driving tractors equipped with GPS and AI explore fields to carry out accurate soil cultivation, enhance soil preparation, and reduce compaction [49]. Robotic planters utilize GPS-guided devices to guarantee precise seed positioning and spacing, hence improving germination rates and crop consistency. Automated systems oversee the transplantation process, guaranteeing that seedlings are positioned at the most advantageous depths and intervals. Utilizing sensor data and AI analysis, drones and robotic sprayers are employed to administer pesticides and fertilizers in a targeted manner, thereby minimizing chemical usage and mitigating environmental consequences [51].

Automated harvesters equipped with advanced visual recognition technology detect mature crops and conduct targeted harvesting, resulting in reduced labor expenses and improved productivity. Automated systems for delivering nutrients monitor the levels of nutrients in the soil and plants and make real-time adjustments to the distribution of fertilizers in order to promote the best possible growth [71]. Smart irrigation systems utilize soil moisture data obtained from sensors to optimize watering schedules, thereby conserving water and ensuring crops receive sufficient hydration. The efficacy of these automated processes is evaluated through field trials, where crop yields, resource utilization, and overall efficiency are compared to conventional farming techniques [72]. The data gathered during these trials provide valuable insights for making ongoing enhancements to the system, hence improving its dependability and effectiveness in real-life agricultural environments.

4. Analysis of existing case studies and applications

This section offers an in-depth investigation and evaluation of previous case studies that demonstrate the practical uses of combining 3D printing, IoT, and AI in precision agriculture. Through the analysis of these case studies, our objective is to determine the primary elements that have contributed to their success, the obstacles they have faced, and the insights gained from their experiences [49]. This analysis will provide vital insights into the practical efficacy of these technologies and establish a basis for future research and development.

4.1. IoT-enabled precision farming

Almond Valley Farms, a prominent almond-producing firm in California, USA, has deployed IoT sensors throughout its extensive fields to continuously monitor environmental factors such as soil moisture, temperature, and humidity in real-time [73]. The sensors were strategically positioned to include the entirety of the field, guaranteeing thorough data acquisition. The deployment of IoT sensors resulted in substantial enhancements in irrigation management. The system facilitated accurate irrigation scheduling by delivering up-to-the-minute information on soil moisture levels, leading to a noteworthy 20% decrease in water consumption and a 15% boost in crop yields. An IoT-based solenoid-controlled pressure regulation system for precision sprayers further underscores the role of IoT in enhancing agricultural efficiency [74]. These enhancements were credited to the capacity to selectively administer water at specific locations and times, minimizing inefficiency and fostering optimal plant development [75]. Notwithstanding the advantages, some obstacles were faced, such as connectivity problems in distant regions and the necessity for frequent sensor calibration to guarantee precision. The main lesson to be learned from this case study is the significance of a strong and resilient IoT infrastructure and dependable network connectivity [76]. **Figure 3** depicts a detailed arrangement of a real-time IoT application that has been installed in a precision agriculture environment.

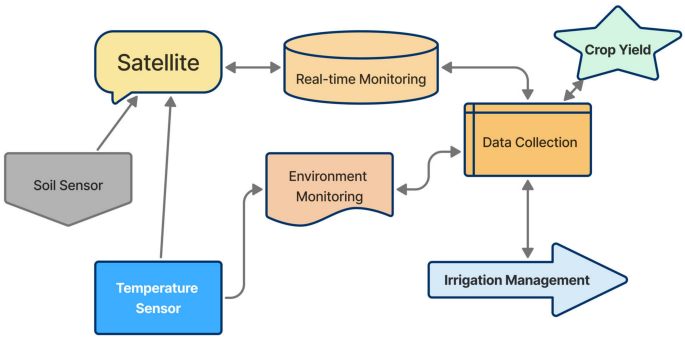

Figure 3 • Real-time IoT application in precision farming.

4.2. AI-driven crop health monitoring

Vino Verde Vineyards in Tuscany, Italy, employed drones outfitted with high-resolution cameras to snap photographs of their grapevines [77]. AI algorithms processed the images in order to find illnesses, pest infestations, and nutrient deficiencies. The AI technology delivered timely alerts regarding potential crop health concerns, enabling farmers to swiftly take action. The use of this proactive strategy resulted in a significant decrease of 25% in crop losses and a notable boost of 10% in overall output [35]. The utilization of AI in crop health monitoring provided a notable benefit by enabling the early identification of issues and facilitating prompt remedial measures [78]. A thorough investigation of machine learning and AI vision applications in all-terrain vehicles for farm automation demonstrates the capacity of AI to significantly change agricultural methods [79]. Various obstacles were recognized, such as the requirement for superior, labeled data to train the artificial intelligence models and substantial computer capacity to handle the vast amounts of image data. This case study highlights the importance of continuously collecting data and refining models to uphold and enhance the accuracy of AI [80]. **Figure 4** illustrates the sequence of steps involved in a crop health monitoring system that utilizes artificial intelligence and drone photography. The procedure involves collecting high-resolution photographs using drones and subsequently analyzing them using AI algorithms to detect diseases, pest infestations, and nutrient deficits.

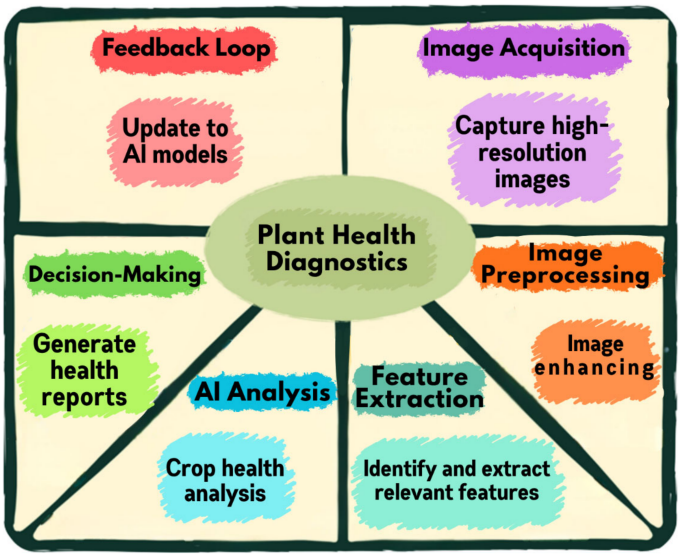

Figure 4 • AI-driven crop health monitoring system.

4.3. Three-dimensional printing of custom sensors

Researchers at the University of Guelph in Ontario, Canada, employed 3D printing technology to fabricate customized sensors designed to meet specific agricultural requirements [81]. The role of 3D printing in designing all-terrain vehicles for farming applications highlights the versatility and potential of this technology in agriculture. The purpose of these sensors is to observe and track the amounts of nutrients in the soil and the surrounding environmental conditions at the university's experimental farm [82]. Implementing 3D-printed sensors led to a notable 30% enhancement in fertilizer management efficiency and a significant 12% rise in crop yields [83]. The rapid prototyping and deployment of tailored sensors conferred a significant benefit, furnishing accurate and pertinent data for the purpose of agricultural management. The challenges included material constraints, since the longevity of the 3D-printed sensors was restricted, requiring frequent replacements and regular upkeep to ensure ongoing precision and operation [84]. This case study showcases the capacity of 3D printing to create cost-effective and personalized sensors for precision agriculture. Nevertheless, improvements in sensor materials and durability are required to augment their lifespan and dependability. **Figure 5** highlights the practical uses and advancements made possible by 3D printing for customized water quality sensor development.

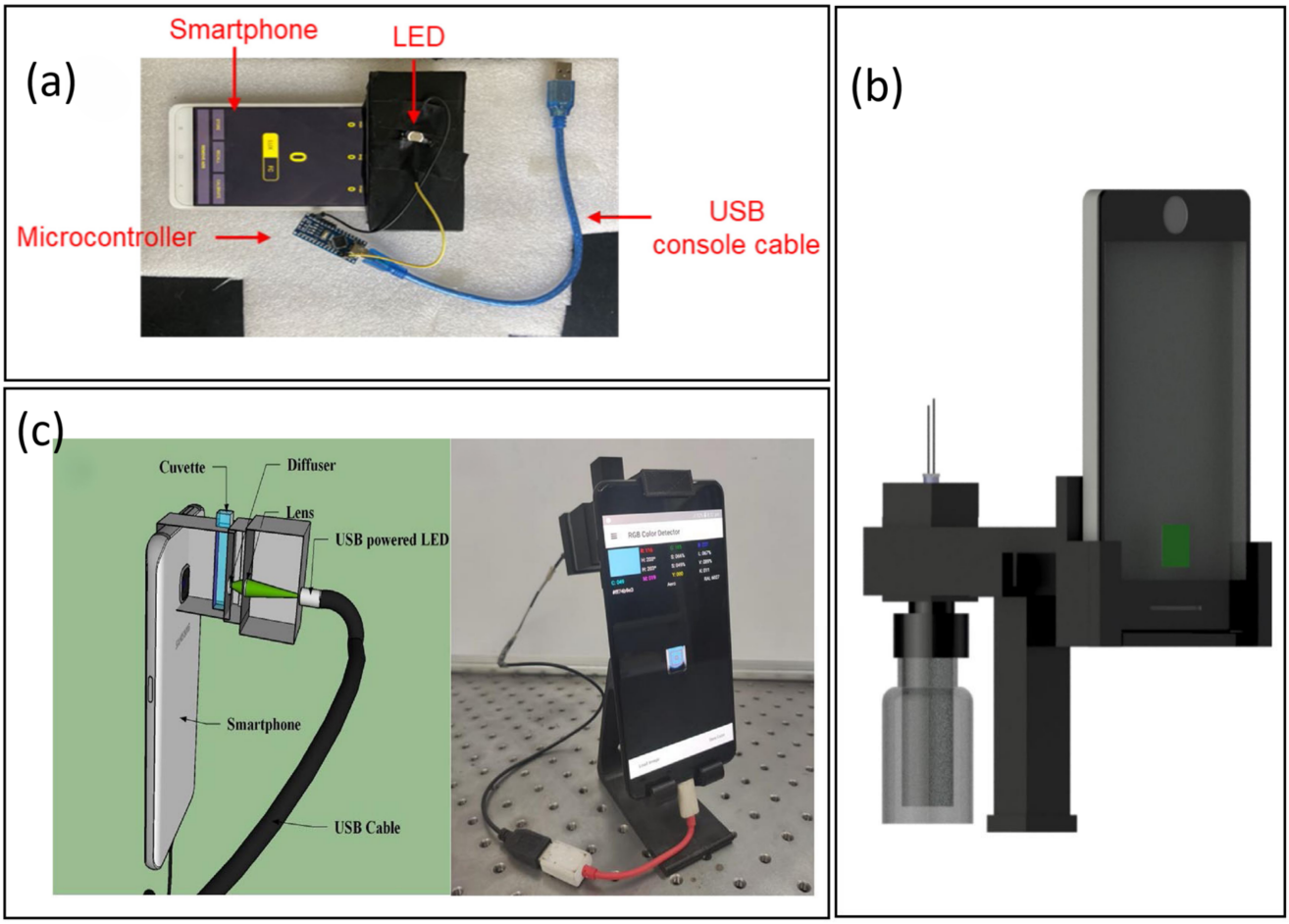

Figure 5 • Three-dimensionally printed water monitoring sensors and accessories: (**a**) Platform for light sensor, (**b**) Determination platform, (**c**) Schematic diagram and photograph. Adapted from [85].

4.4. IoT and AI integration for livestock monitoring

Outback Ranch in Queensland, Australia, implemented IoT and AI technologies to monitor their livestock [86]. Wearable IoT devices were employed to monitor the well-being and physical activity of cattle, while AI algorithms scrutinized the collected data to identify health problems and enhance feeding timetables. The convergence of IoT and AI has led to enhanced animal health management. Timely identification of health problems resulted in prompt veterinarian interventions, resulting in a 20% decrease in fatality rates. Enhanced weight gain efficiency and overall productivity were achieved through optimized feeding schedules [87]. An IoT-based semi-autonomous vehicle sprayer developed for precision agriculture exemplifies the synergy between IoT and AI technologies in enhancing farm operations [88]. The challenges involved guaranteeing the robustness and comfort of wearable devices for cattle, as well as combining data from various devices to ensure seamless compatibility. This case study emphasizes the significance of long-lasting, pleasant wearable devices and strong data integration platforms for effective livestock monitoring [89]. **Figure 6** shows the combination of IoT and AI technologies to monitor the health and activity of animals. The installation displays wearable IoT devices that are attached to animals to gather data on their locomotion, health indicators, and behavioral patterns. The AI algorithms analyze the data to identify health problems and improve feeding schedules.

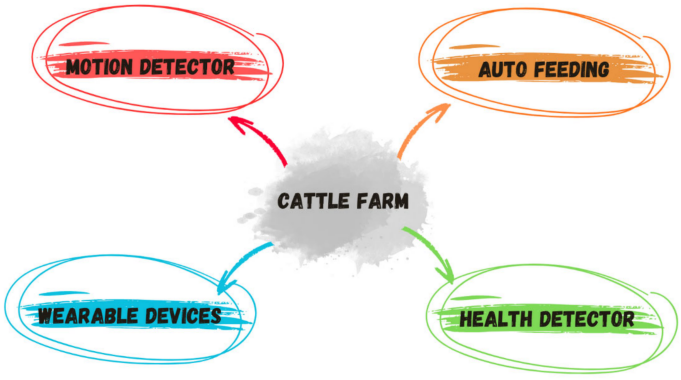

Figure 6 • Integration of IoT and AI in livestock monitoring.

4.5. AI-powered pest management

A joint initiative between the Indian Agricultural Research Institute and local farmers in Rajasthan, India, employed artificial intelligence and image processing techniques to effectively monitor and control pest populations in agricultural areas. Drones took high-resolution pictures, and AI systems found pest hotspots and then suggested specific actions [90].

The implementation of the pest control system, which utilizes artificial intelligence, resulted in a significant decrease of 30% in the utilization of pesticides. It led to a notable improvement of

15% in the productivity of crops. By focusing on areas with high pest activity, farmers can optimize the application of pesticides, resulting in a more effective use of resources and a reduction in both environmental harm and expenses [91]. The challenges encompassed the need to ensure precise identification of pests by the AI algorithms while minimizing false positives, as well as the substantial upfront expenses associated with the deployment of drones and AI technology. This case study underscores the importance of precise AI algorithms and showcases the financial advantages of focused pest control, despite the significant upfront expenses associated with its implementation. **Figure 7** presents a comprehensive workflow of a pest management system that utilizes artificial intelligence. It describes the process of utilizing drones to capture high-resolution photos of crops, followed by the application of AI algorithms to analyze these images and identify areas with significant pest activity. Based on this analysis, specific treatments are recommended to address the identified pest hotspots.

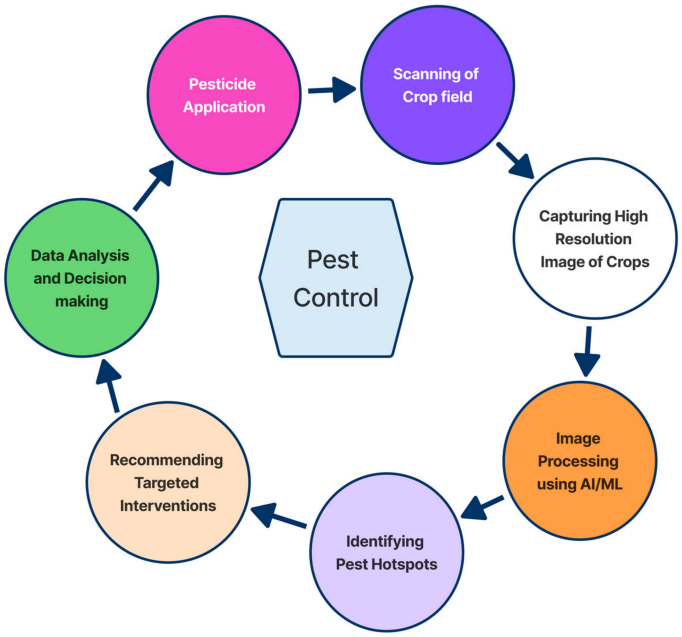

Figure 7 • AI-powered pest management system.

4.6. Three-dimensionally printed equipment parts

Farms in Iowa, USA, utilized 3D printing technology to fabricate tailor-made components for their agricultural machinery. This method facilitated the rapid development and manufacturing of components that were otherwise challenging to obtain. Implementing 3D-printed components resulted in a 40% decrease in equipment downtime and a 25% reduction in maintenance expenses [92]. A review of the future of agriculture with automatic all-terrain vehicles in precision farming highlights the importance of advanced technologies in modern agriculture [93]. Farmers have the ability to efficiently manufacture and substitute components, guaranteeing uninterrupted functioning during crucial farming periods. The challenges encompassed ensuring the 3D-printed components possessed the requisite strength and durability, as well as necessitating farmers to possess expertise in 3D printing technology [94]. This case study illustrates the capacity of 3D printing to decrease equipment downtime and lower maintenance expenses. Nevertheless, there is a requirement for more robust materials and comprehensive training for farmers in the field of 3D printing technology.

Figure 8 consolidates quantitative performance data from various applications of 3D printing, IoT, and AI in precision agriculture. It clearly demonstrates significant improvements in crop yields, resource efficiency (water, fertilizer, pesticides), and operational aspects (downtime, maintenance costs).

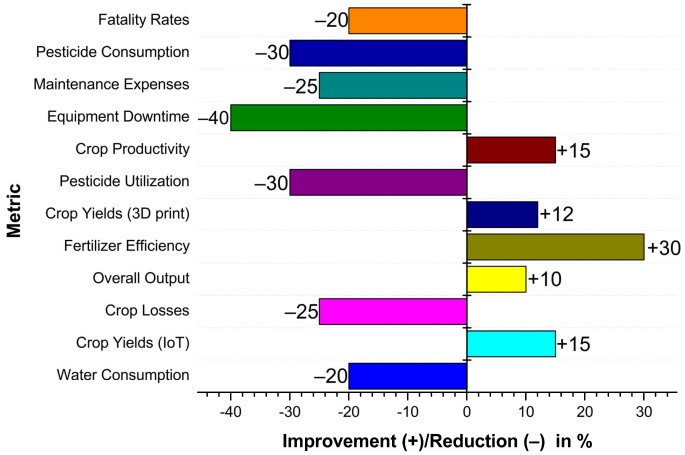

Figure 8 • Comparative performance of advanced agricultural technologies and applications.

5. Critical analysis and synthesis

The reviewed literature reveals a comprehensive exploration of 3D printing, IoT, and AI technologies in precision agriculture, highlighting their individual and combined potentials for enhancing productivity, sustainability, and resource efficiency. A recurring theme is the promising integration of these technologies to address complex agricultural challenges, yet significant gaps remain in scalability, interoperability, and cost-effectiveness. While many studies demonstrate innovative prototypes and frameworks, the robustness of methodologies and real-world applicability often require further validation. Additionally, challenges such as data management, infrastructure limitations, and socio-economic barriers are frequently acknowledged but insufficiently addressed, indicating areas for future research and development.

Unlike many recent reviews that primarily examine AI and IoT applications, the unique contribution of this study lies in its explicit emphasis on the role of 3D printing. By integrating additive manufacturing with digital agriculture, the review highlights how 3D printing can accelerate the customization and prototyping of agricultural sensors, making them adaptable to diverse environments and farm-specific needs. This interdisciplinary lens, bridging digital data systems and fabrication technologies offers a perspective not fully explored in earlier reviews, thus enriching the discourse on precision agriculture.

5.1. Technological innovation and application

The literature showcases significant advancements in 3D printing for creating customized agricultural components and sensor housings, demonstrating durability and adaptability under diverse conditions [95, 96]. IoT applications provide real-time monitoring and control of environmental variables, enhancing

automation and resource management [97–99]. AI contributes predictive analytics and decision-making tools for crop management, disease detection, and yield forecasting [100–102]. Their convergence supports the development of AI-driven digital twins and integrated sensor networks [103–105].

However, most reported systems remain at the prototype level, with limited validation at scale [106, 107]. Diverse agricultural contexts and environmental variability challenge the generalizability of solutions [101, 108]. Furthermore, seamless integration of 3D printing, IoT, and AI is underexplored, with interoperability gaps persisting [109, 110].

5.2. Methodological rigor and data quality

Several studies employ robust experimental designs, including long-term sensor testing and benchmarking against commercial tools, enhancing reliability [95, 98]. AI models are often trained on multisource datasets, improving prediction accuracy [101, 111]. Cloud platforms and real-time analytics support dynamic decision-making and adaptability [112, 113]. Yet, methodological weaknesses persist. Many AI systems lack explainability, hindering trust and transparency [102]. Sensor calibration, data noise, and missing values are often overlooked [83, 111]. Heavy reliance on simulation studies further limits insights into real-world variability [106, 114].

5.3. Environmental and economic impact

The integration of IoT and AI technologies has been shown to reduce water usage, fertilizer application, and pesticide waste, thereby advancing environmental sustainability [100, 115]. Energy-efficient frameworks such as Green-IoT and photovoltaic-powered systems contribute to minimizing carbon footprints [97]. Economic analyses suggest potential cost savings and labor reduction [102]. However, long-term life-cycle assessments remain scarce [116, 117]. Initial investment costs, maintenance, and training expenses are often underestimated, creating barriers for smallholder farmers [118]. The environmental benefits of 3D printing are promising but require further comparative analyses against traditional manufacturing [96, 119].

5.4. Integration benefits

This review distinguishes itself from earlier state-of-the-art studies by explicitly focusing on the integration of 3D printing with AI and IoT in precision agriculture. While most reviews emphasize digital technologies such as IoT-based monitoring systems or AI-driven analytics, they rarely address how additive manufacturing can contribute to customization, affordability, and rapid prototyping of agricultural sensors [110, 112]. By bridging digital data systems with fabrication technologies, this work highlights a novel interdisciplinary pathway that has not been fully explored in the prior literature.

The incorporation of 3D printing, IoT, and AI in precision agriculture has demonstrated measurable efficiency improvements. Automated systems minimize the requirement for human effort, enabling more effective utilization of resources [7]. IoT-enabled monitoring improves irrigation schedules, reducing water waste and increasing crop output, while AI-driven crop health monitoring enables early detection of nutrient deficiencies, pests, and diseases for timely interventions. For example, studies on electrode materials for soil fertilizer content measurement highlight the potential of precision agriculture in optimizing nutrient management [120]. Furthermore, precision agriculture promotes targeted use of water, fertilizers, and pesticides, reducing environmental footprints while maintaining or improving crop productivity [121]. By combining real-time data with predictive analytics, farmers can ensure optimal growing conditions throughout the crop cycle [122].

5.5. Challenges and limitations

Despite the growing enthusiasm for integrating AI, IoT, and 3D printing into agriculture, several challenges remain.

5.5.1. Sequence of adoption

Agricultural digitalization should follow a stepwise pathway. IoT provides the foundation by generating real-time data. Without robust datasets, AI algorithms cannot function effectively [123]. Once reliable datasets are available, AI-driven analytics can optimize irrigation, nutrient management, and pest control. Only after these stages are established should 3D-printed customization of sensors and components be introduced to avoid premature investments.

5.5.2. Cost–benefit considerations

Economic feasibility remains a major barrier. Large-scale farms benefit from economies of scale, lowering per-hectare costs of IoT networks and AI systems [124, 125]. However, smallholders face high upfront costs, fragmented landholdings, and limited technical capacity, reducing return on investment [126]. Policy mechanisms such as subsidies, cooperative models, and shared-service platforms are essential to bridge this digital divide.

5.5.3. Farmer-oriented adoption strategies

Technology adoption is incremental, and farmer acceptance is critical. A modular strategy—beginning with low-cost IoT soil or crop health sensors, followed by AI advisory tools, and finally 3D-printed customization—reduces risk and builds confidence. Training, extension support, and intuitive user interfaces further enhance adoption success [127, 128].

5.5.4. Policy and EU CAP alignment

At the policy level, integration must align with sustainability frameworks. In Europe, the Common Agricultural Policy (CAP) prioritizes reduced environmental impact, improved resource efficiency, and farm digitalization [129]. AI, IoT, and 3D printing can directly support these goals, but coordinated investment, farmer incentives, and monitoring systems are required to ensure technologies contribute to sustainability and resilience [130]. **Table 2** below outlines the challenges alongside technological and policy-driven solutions.

Table 2 • Challenges and solutions in smart farming technology integration.

Challenge	Affected technology	Description	Proposed solution or innovation	References
High initial investment	3D printing, IoT, AI	Costly equipment and infrastructure	Government subsidies, low-cost hardware R&D	[131]
Technical skill requirement	All	Farmers lack training in tech systems	Capacity building, training programs	[132]
Connectivity in rural areas	IoT	Weak or no internet signal in farms	Use of LPWAN, satellite IoT networks	[133]
Sensor durability and accuracy	3D-printed sensors	Inconsistent readings, environmental wear	Use of weatherproof materials, periodic calibration	[134]
Data security and privacy	IoT, AI	Risk of misuse or loss of collected farm data	Blockchain integration, secure cloud frameworks	[135]
Limited dataset availability	AI	AI needs large datasets to learn effectively	Collaborative open data platforms	[136]
Interoperability of systems	IoT + AI + 3D printing	Devices from different vendors do not work well together	Development of universal integration protocols	[137]
Environmental sustainability	3D printing materials	Some 3D printing materials are not biodegradable	R&D on bio-based printable materials	[138]
Maintenance and power requirements	IoT, Drones, Robots	Sensors and devices need frequent charging/repairs	Solar-powered systems, energy-efficient design	[139]

5.6. Future directions and innovations

Emerging trends include the integration of 5G, edge computing, blockchain, and digital twins to improve efficiency and transparency [103, 140]. Explainable AI and sustainable IoT frameworks are gaining momentum [110, 115]. The convergence of robotics, AI, and additive manufacturing is expected to revolutionize agricultural automation [104, 109]. Yet research gaps persist in data privacy, ethical implications, and socio-economic impacts [124]. Interdisciplinary collaboration and robust policy frameworks are urgently needed. **Figure 9** illustrates the technological synergy across IoT, AI, and 3D printing, emphasizing their intersecting roles in smart farming systems.

5.7. Synthesis of key findings

Integrating 3D printing, IoT, and AI is central to advancing efficient, sustainable, and adaptive farm management [141]. These technologies complement each other, with IoT providing data, AI enabling analytics, and 3D printing facilitating customization of tools and sensors. Together, they create synergistic systems that can significantly transform agricultural practices [142].

This review offers valuable insights for researchers, practitioners, and policymakers by consolidating recent case studies and identifying critical gaps [143]. Addressing barriers such as high costs, interoperability issues, and policy alignment will be essential to scaling these innovations across diverse farming contexts. Ultimately, the convergence of digital and fabrication technologies provides a pathway toward resilient, resource-efficient, and environmentally responsible agriculture.

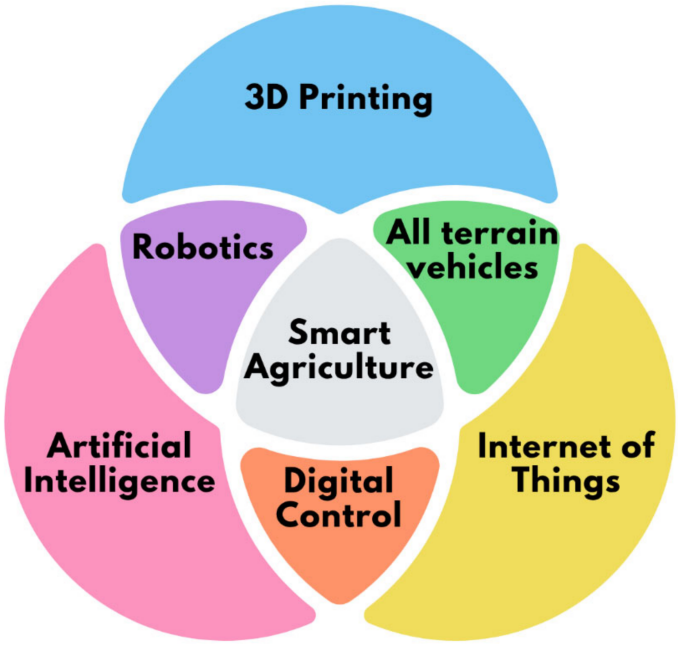

Figure 9 • Technological synergy in precision agriculture.

6. Conclusions

The incorporation of 3D printing, IoT, and AI technologies in precision agriculture has demonstrated measurable improvements in efficiency, productivity, and sustainability. Studies report that the use of 3D-printed sensors has enabled real-time soil and crop monitoring with accuracy levels exceeding 90%, while reducing

fabrication costs by 20–30% compared to conventional manufacturing. IoT networks have been shown to reduce water usage in irrigation by up to 25% through optimized scheduling, while maintaining consistent connectivity across fields spanning several hundred hectares. Artificial intelligence and image processing algorithms have achieved disease and nutrient stress detection rates of 85–95%, allowing for timely interventions and improved crop health outcomes. The integration of these technologies has also demonstrated substantial operational benefits. Automated farm operations have reduced labor costs by 15–25% and shortened operational durations by nearly 30%, ensuring consistent performance under diverse environmental conditions. Field-level implementations show yield improvements of 10–20%, alongside a 15–40% reduction in chemical inputs, contributing directly to enhanced soil health and lower environmental footprints compared with conventional farming practices.

Despite these advances, adoption remains constrained by challenges such as high initial investment (often ranging from USD 5000 to 15,000 for basic IoT- and AI-integrated setups) and the requirement for specialized technical expertise. These barriers particularly affect smallholder farmers, who also face unreliable rural internet connectivity. Addressing these gaps will require affordable, modular solutions, supportive policies, financial incentives, and capacity-building programs to broaden accessibility. Future research must prioritize improving the durability of 3D-printed agricultural components, enhancing data security and interoperability across platforms, and developing AI models that are both transparent and adaptable to dynamic agro-climatic conditions. By addressing these concerns, the integration of AI, IoT, and 3D printing can help align agricultural practices with global sustainability goals, ultimately reducing the carbon footprint of farming activities by an estimated 10–15%. This review consolidates current knowledge, highlights integration pathways, and underscores both opportunities and limitations, making it a valuable reference for researchers, practitioners, and policymakers engaged in shaping the future of smart and sustainable agriculture.

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